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MODELING THE PROBABILITY OF INDIVIDUAL TREE MORTALITY

David A. Hamilton, Jr., and
Bruce M. Edwards

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$$CR = f_e[CCF\cdot\cdot]$$

$$B = \frac{1}{\sqrt{2\pi}} \int_a^b x e^{-x^{3/2}} dx$$

$$\ln[\Delta H] = f_N[\Delta D, H, D]$$

$$MORT = \frac{1}{1 + \exp[-B_1 X_i]}$$

$$\ln[BAI] = f_B[D.b.h., Habitat, Crown]$$

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ABSTRACT

This paper describes procedures for developing and testing models that predict the probability of individual tree mortality. The modeling procedures include data screening, parameter estimation, and model verification techniques that have been designed to deal with dichotomous dependent variables. To demonstrate the procedures, mortality models for 10 north Idaho species are developed and verified.

INTRODUCTION

Because mortality is an important component of stand development, models that predict mortality over time must be included in systems that project stand growth. The mortality models described in this paper were developed for a stand growth prognosis model devised by Stage (1973). Other stand growth models, such as those developed by Myers (1973), Lin[1], Stiell[2], and Bartos[3], also require some form of mortality model to deal with the mortality component of stand development.

The mortality model can be used to help schedule management activities. Stands of trees for which the model predicts high mortality rates should be considered high risk stands susceptible to insect and disease outbreaks and should be logged, salvaged, or otherwise treated before stands composed of trees with low predicted mortality rates.

Mortality models also reveal relationships that may provide a better understanding of how and why mortality occurs in a stand. This information is valuable in management planning and in developing strategies to control mortality.

The models discussed in this paper were developed by means of a three-step analysis. The first step is to screen the independent variables for those that show the strongest relationships to the probability of mortality. The variables selected as most significant by the screening algorithm are used as predictors of the probability of mortality in a logistic model. The regression coefficients for this model are then estimated by a nonlinear regression program, RISK (Hamilton 1974). The final step, model verification, employs a chi-square statistic to evaluate the accuracy with which the proposed model predicts the mortality that occurred on an independent data set.

---

[1]Lin, Jim Y. 1973. Stand growth simulation models for Douglas-fir and western hemlock in the northwestern United States. Paper presented at Joint Meeting of Subject Groups S4.01 and S6.02, Int. Union For. Res. Organ., Vancouver, B.C., Can., Aug. 20-24, 1973.

[2]Stiell, W. M. 1973. An application of stand volume and tree mortality models in yield table construction. Paper presented at Joint Meeting of Subject Groups S4.01 and S6.02, Int. Union For. Res. Organ., Vancouver, B.C., Can., Aug. 20-24, 1973.

[3]Bartos, Dale L. 1973. A dynamic model of aspen succession. Paper presented at Joint Meeting of Subject Groups S4.01 and S6.02, Int. Union For. Res. Organ., Vancouver, B.C., Can., Aug. 20-24, 1973.

PROPERTIES OF MORTALITY MODELS

Models can be developed to predict either stand mortality or the mortality of individual trees within the stand. The models discussed in this paper were developed to predict individual tree mortality within a specified time interval as a function of stand and individual tree characteristics. The true probability of mortality is bounded by 0 and 1. Thus, it would be desirable for the mortality model to provide estimates of probability in the interval [0,1].

A linear regression model frequently has been used for this purpose. However, a linear model cannot insure that probability estimates will be in the interval [0,1]. In addition, using a linear regression model for this purpose creates many statistical problems (Hamilton 1974).

Walker and Duncan (1967) and Neter and Maynes (1970) have suggested that the logistic function, which limits estimates of probability to the interval [0,1], is the statistically preferred model for expressing the relationship between a 0,1 dependent variable and a set of independent variables. For this reason, we have used a logistic function for modeling mortality.

DATA REQUIREMENTS FOR MORTALITY MODELING

Large quantities of individual tree data must be available to fit mortality models that predict the probability of an individual tree dying within a specified interval. Individual tree characteristics on sample trees must be measured at the beginning of the interval. The status of the tree, that is, whether it is alive or dead, must be recorded at the end of the interval.

Mortality models from such data are directly applicable only for the interval and geographic area actually measured. We extend model capability by distributing plots over the geographic range of interest and by measuring them over several successive intervals. Variability in mortality rates that is caused by uncontrollable climatic factors may be accounted for in two ways. Plots may be measured at intervals of at least 5 to 10 years in order to include a range of climatic conditions within the measurement interval. Alternatively, plots may be remeasured at shorter intervals. For example, we could measure trees annually for 10 to 20 years and record mortality when it occurs. When this is done, variability in mortality rates caused by climatic variation is accounted for by the fact that a range of climatic conditions is represented in the data set used for modeling.

The time span required to gather data is often longer than we can afford; thus, we frequently work with available data. To do this, geographic range, distribution of sample trees, and time span must be representative of the target population. When this is not the case, we must recognize and state the limitations of the resulting models.

Models reported in this paper reflect processes or conditions in the forest at the time the data were collected. False mortality estimates may result when the equations are applied to trees growing under different conditions. For example, during the data gathering period mortality from white pine blister rust (*Cronartium ribicola*) and from the mountain pine beetle (*Dendroctonus monticolae*) were at epidemic levels. Thus, the mortality model reported in this paper will produce high levels of mortality in western white pine (*Pinus monticola*). Models for other species reported in this paper do not appear to produce abnormal mortality rates for the species involved. However, as the dynamics of the north Idaho forests change, the models will require continual updating.

Data Used in This Study

Data were collected over two periods on Potlatch Corporation permanent variable-radius plots, using a 25-factor prism. In the first measurement period (1964-1970), part of the data was measured over a 5-year interval and the remainder was measured over a 3-year interval. In the second measurement period (1968-1974), data were recorded over a 6-year interval.

MODELING METHODS

Data Screening

The first step is to screen the independent variables for those that best explain variations in the dependent variable (mortality rate).

In the model to be fit to the data, the dependent variable is dichotomous: the value 0 is assigned to green trees, the value 1 to dead trees. For model fitting, probability of mortality for an individual tree is not considered; a specific tree is either alive or dead. The analytical method enables us to use all trees with similar characteristics (independent variables) to estimate the probability of mortality for a tree with these characteristics.

In fitting the model, we assume that each tree is an independent observation. Thus, we ignore the fact that there is some clustering in the selection of sample trees. However, in most instances the model will be applied to stands; thus, the impact of clustering, and of the resulting nonindependence of observations, is reduced.

The algorithm used in this screening process has been developed specifically for situations in which the dependent variable is dichotomous. SCREEN, the computer program that does the screening, is described by Hamilton and Wendt (1975). The theoretical development of the algorithm and the statistic used for screening are discussed by Gleser and Collen (1972) and by Sterling and others (1969).

Data were divided into two parts: data screening and parameter estimation were done with data collected in the first measurement period; models were verified by means of data collected in the second measurement period.

Age, diameter breast high, height, crown class, basal area per acre of the stand, percent defect, and diameter growth rate prior to mortality were the variables in the data set which were considered potential predictors of mortality. Instructions for estimating percent defect as specified in "Instructions for Forest Inventory of Potlatch Forests, Inc. Logging Units" as revised July 8, 1959, are reproduced in the appendix. SCREEN was run independently for each of the 10 north Idaho species included in this study.

Output from SCREEN consists of a tree diagram showing characteristics that best predict mortality. SCREEN also reports how mortality rate changes over the range of these predictors.

We have considered three levels of significance: a high level (95 percent), a moderate level (75 percent), and a low level (50 percent). The objective of data screening is to identify combinations of independent variables that are related to the probability of mortality. By including the 75 and 50 percent significance levels, we were able to gain a better understanding of the relationships that exist between the probability of mortality and the set of independent variables. However, only independent variables significant at the 95 percent level were included in the models developed in this study.

An example of the use of SCREEN to develop tree mortality predictors for grand fir (*Abies grandis*) follows. The SCREEN output for this example is displayed in figure 1. At the 95 percent significance level two tree characteristics, percent defect and crown class, are significant predictors of tree mortality. The output indicates that grand fir trees with defect percent from 0 to 90 have a 5-year mortality rate of 81/1523 = 0.053, while trees with 91 to 100 percent defect have a mortality rate of 36/259 = 0.139. Additionally, among trees with percent defect of 0 to 90 percent, those with crown class of 1, 2, or 3 (dominant, codominant, intermediate) have a mortality rate of 58/1310 = 0.044, while trees with crown class 4 (suppressed) have a mortality rate of 23/213 = 0.108.

At the 75 percent significance level, the significant predictors are percent defect, crown class, diameter, and age. At the 50 percent significance level, the significant predictors are the same as the predictors at the 75 percent level of significance. This implies that only a negligible amount of the unexplained variation can be explained by any of the unused independent variables.

Parameter Estimation

Once the "optimal" set of independent variables has been selected, it is necessary to estimate the parameters of the mortality model. The general form of the logistic mortality model is

$$P = \{1 + \exp [-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots)]\}^{-1}$$

where

P = probability of mortality in a specific time interval

β_i = ith nonlinear regression coefficient (model parameters), i = 0,1,...

x_j = jth independent variable, j = 1,2,...

Figure 1.-SCREEN output of potential mortality predictors for grand fir.

```
MORTALITY STUDY FOR GRAND FIR                    50% SIGNIFICANCE LEVEL

                                                 AGE OF TREE
                                                     1-2
                                                     3-5
                                                     6-8
                                 CROWN CLASS         9-12
                                     1               ........
                                     2               .000701.
                 % DEFECT            3               .000039.
                     0-20            ........        ........
                     21-35           .001252.        13-19
                     36-50           .000058.        20+
                     51-60           ........        ........
                     61-70                           .000551.
                     71-80                           .000019.
                     81-90                           ........
                     ........
                     .001442.        4
KIND                 .000081.        ........
    LIVE             ........        .000190.
    DEAD                             .000023.
    ........                         ........
    .001665.
    .000117.
    ........                     DIAMETER
                                     0.0-3.0
                                     3.1-6.0
                                     6.1-9.0
                                     ........
                     91+             .000031.
                     ........        .000010.
                     .000223.        ........
                     .000036.        9.1-12.0
                     ........        12.1-15.
                                     15.1-18.
                                     18.1-30.
                                     30.1+
                                     ........
                                     .000192.
                                     .000026.
                                     ........
```

MORTALITY STUDY FOR GRAND FIR 75% SIGNIFICANCE LEVEL

AGE OF TREE

1-2
3-5
6-8
9-12
.....
.000701.
.000039.
.....
13-19
20+
.....
.000551.
.000019.
.....

CROWN CLASS

1
2
3
.....
.001252.
.000058.
.....
4
.....
.000190.
.000023.
.....

% DEFECT

0-20
21-35
36-50
51-60
61-70
71-80
81-90
.....
.001442.
.000081.
.....
91+
.....
.000223.
.000036.
.....

KIND

LIVE
DEAD
.....
.001665.
.000117.
.....

DIAMETER

0.0-3.0
3.1-6.0
6.1-9.0
.....
.000031.
.000010.
.....
9.1-12.0
12.1-15.
15.1-18.
18.1-30.
30.1+
.....
.000192.
.000026.
.....

MORTALITY STUDY FOR GRAND FIR 95% SIGNIFICANCE LEVEL

CROWN CLASS

1
2
3
.....
.001252.
.000058.
.....
4
.....
.000190.
.000023.
.....

% DEFECT

0-20
21-35
36-50
51-60
61-70
71-80
81-90
.....
.001442.
.000081.
.....
91+
.....
.000223.
.000036.
.....

KIND

LIVE
DEAD
.....
.001665.
.000117.
.....

The RISK computer program (Hamilton 1974) is a nonlinear regression program that efficiently estimates the parameters. This program was used to estimate the β_i for those independent variables selected for inclusion in the model by the data screening procedure.

Because the sampling probability for each observation in the data set was proportional to $(DBH)^2$, each observation was assigned a weight proportional to the inverse of $(DBH)^2$ in RISK. To model annual mortality rates from a data set that included two unequal length time intervals, the dependent variable associated with each observation was divided by the appropriate time interval.

A model developed from data measured over a specific time interval produces mortality rate estimates that are applicable only to similar time intervals. This could be a severe limitation when we wish to predict the probability of mortality for a range of time intervals. The limitation can be partially overcome by considering mortality rate to behave like compound interest. The model can then be used to predict mortality for any measurement interval, and data sets with unequal remeasurement intervals can be used for model verification. Because we chose a 1-year base for this analysis, mortality functions from RISK will predict annual mortality rate.

In the following derivation, mortality rate is treated as a negative interest rate. The standard compound interest formula (1) may be used to calculate the number of surviving trees over any desired time interval.

$$V_n = V_o\ (1-r)^n \tag{1}$$

where

V_n = number of trees living after n years

V_o = number of trees living today

r = annual mortality rate

n = number of years in prediction interval.

This formula may be applied directly when the mortality rate is an annual rate. Algebraic manipulation of formula (1) produces the following formula that converts an annual mortality rate to an n-year mortality rate:

$$\frac{V_n}{V_o} = (1-r)^n$$

$$\Rightarrow \quad \frac{V_o - V_n}{V_o} = 1-(1-r)^n$$

$$\Rightarrow \quad P_n = 1-(1-r)^n \tag{2}$$

When the mortality rate is for a period of n years, the following formula, derived from equations (1) and (2), should be used to calculate mortality:

$$V_{n*} = V_o\ (1-P_n)^{n*/n} \tag{3}$$

where

V_{n^*} = number of trees living after n^* years

V_o = number of trees living today

P_n = mortality rate based on an n year interval

n = number of years used as basis for estimating P_n

n^* = number of years for which prediction is desired.

Algebraic manipulation of formula (3) produces the following formula that converts an n-year mortality rate to an n^*-year mortality rate:

$$\frac{V_{n^*}}{V_o} = (1-P_n)^{n^*/n}$$

$$\Rightarrow \quad \frac{V_o - V_{n^*}}{V_o} = 1 - (1-P_n)^{n^*/n}$$

$$\Rightarrow \quad P_{n^*} = 1-(1-P_n)^{n^*/n} \qquad (4)$$

Continuing with the grand fir example, the mortality probability prediction model from RISK is as follows:

$$\hat{P}_i = 1.0/\{1.0 + \exp[4.89819 - 0.0047554(\%DEF_i) - 0.222746(CC_i)]\}$$

where

$\hat{P}_i$ = predicted annual mortality rate for tree i

$\%DEF_i$ = percent defect in tree i

CC_i = crown class of tree i

In this model, the qualitative variable crown class is used as if it were a continuous variable. Because we would expect a constant increase in mortality rate as crown class changes from dominant to suppressed (1 to 4), using crown class in this manner should cause few problems.

This model predicts the probability that an individual grand fir tree will die in a given year as a function of percent defect and crown class. Thus, for codominant grand fir (CC_i = 2) with 25 percent defect, the probability of mortality in the following year is:

$$\hat{P}_i = 1.0/\{1.0 + \exp[4.89819 - 0.0047554(25.0) - 0.222746(2)]\}$$

$$= 1.0\{1.0 + \exp[4.89819 - 0.11888 - 0.44549]\}$$

$$= 1.0/[1.0 + \exp(4.33382)]$$

$$= 1.0/77.23494$$

$$= 0.01295$$

This tree would have a 1.29 percent chance of dying during a 1-year period. This yearly mortality rate will change as the tree parameters, percent defect and crown

class, change. As percent defect becomes greater, the probability of mortality increases. If the tree's crown class changes to a dominant position, its probability of mortality will decrease, while a change to an intermediate or suppressed crown class will increase its probability of mortality.

Model Verification

The models discussed must be verified before being employed to describe mortality in a stand over time. Verification tests whether the proposed model does more than reproduce peculiarities of a specific set of data.

"Goodness of fit" of the models was tested by means of the chi-square statistic

$$\chi^2 = \sum_{i=1}^{n} (O_i - E_i)^2 / E_i$$

where

O_i = observed number of mortality trees falling in the ith class

E_i = expected number of mortality trees falling in the ith class

n = number of classes

χ^2 = chi-square statistic

A computer program was written for verifying the proposed models with the chi-square statistic. The population is divided into twenty-one 2-inch diameter classes that range from 0-2 inches to >40 inches. The verification program uses the nonlinear regression model developed with the aid of RISK to predict the probability of mortality for each observation in the population being used for validation. Goodness of fit of the model is determined by using the chi-square statistic to compare the observed number of dead trees in each 2-inch diameter class with the expected (predicted) number of dead trees in the class.

The set of data for verifying the models from RISK has a remeasurement interval of 6 years. Thus, it was necessary to use the compound interest formula to convert the annual probability of mortality predicted by the model to the probability of mortality over the measurement interval.

The results of model verification of the grand fir model developed by RISK are presented in table 1. We will use line 3 of table 1 to explain the output. Class 3 contains all trees from 4 to 6 inches d.b.h. This class contains 73 trees (col. 4) or 4.74 percent (col. 3) of the population. The probability of mortality for each tree in the class is summed to obtain the expected number of trees that will die. Of the 73 trees in class 3, 7.2 trees (col. 6) are expected to die. Eight of these trees (col. 5) actually died. The chi-square statistic comparing these values is reported in column 7. The sum of the chi-square statistics for all diameter classes is the measure of goodness of fit for the model. At the 95 percent confidence level, the tabulated chi-square statistic for 21 degrees of freedom is 32.7. Since the calculated chi-square value of 26.73 is less than the tabulated value, we cannot reject the model at the 95 percent confidence level.

Table 1.--*Model verification for grand fir model*

Class (1)	Interval (2)	Percentage in interval (3)	Number in interval (4)	Observed mortality (5)	Predicted mortality (6)	Chi-square statistic (7)
1	0.00 - 2.00	1.69	26.0	3.0	2.6	0.06
2	2.00 - 4.00	4.55	70.0	5.0	6.9	0.52
3	4.00 - 6.00	4.74	73.0	8.0	7.2	0.09
4	6.00 - 8.00	6.50	100.0	10.0	9.7	0.01
5	8.00 - 10.00	7.73	119.0	7.0	10.5	1.17
6	10.00 - 12.00	6.82	105.0	3.0	9.1	4.09
7	12.00 - 14.00	7.41	114.0	5.0	9.8	2.35
8	14.00 - 16.00	6.95	107.0	7.0	8.4	0.23
9	16.00 - 18.00	5.39	83.0	7.0	6.2	0.10
10	18.00 - 20.00	6.24	96.0	3.0	7.6	2.78
11	20.00 - 22.00	5.00	77.0	2.0	6.1	2.76
12	22.00 - 24.00	5.13	79.0	8.0	6.0	0.67
13	24.00 - 26.00	4.09	63.0	7.0	4.8	1.01
14	26.00 - 28.00	4.35	67.0	7.0	5.2	0.62
15	28.00 - 30.00	4.94	76.0	5.0	5.7	0.09
16	30.00 - 32.00	5.00	77.0	8.0	6.0	0.67
17	32.00 - 34.00	3.96	61.0	9.0	4.7	3.93
18	34.00 - 36.00	2.66	41.0	3.0	3.2	0.01
19	36.00 - 38.00	1.82	28.0	1.0	2.2	0.65
20	38.00 - 40.00	2.27	35.0	6.0	2.9	3.31
21	40.00+	2.73	42.0	1.0	3.3	1.60
Total			1,539.0			26.73

MORTALITY PREDICTION FOR NORTH IDAHO SPECIES

Mortality prediction models were developed for five tree species in north Idaho. Models for western white pine, western larch (*Larix occidentalis*), Douglas-fir (*Pseudotsuga menziesii*), grand fir, and western redcedar (*Thuja plicata*) are reported in table 2. For each species, table 2 reports the prediction equation, the number of observations used in the analysis, and the means and standard deviations for diameter at breast height and for variables used in the prediction equations. The means and standard deviations of the variables are reported so users are aware of the limitations of the models and to enable users to select populations to which the models may be applied with confidence.

In table 3, annual mortality rates are reported for western hemlock (*Tsuga heterophylla*), lodgepole pine (*Pinus contorta*), Engelmann spruce (*Picea engelmannii*), subalpine fir (*Abies lasiocarpa*), and ponderosa pine (*Pinus ponderosa*) in north Idaho. Because of limited data and low mortality rates no significant predictors of mortality were found for these species; therefore, only annual mortality rates are reported for these five species. The number of observations, and the mean and standard deviation of the diameter distribution are reported for each species to indicate limitations of the data.

The "optimal" models for grand fir and western redcedar use the variables, crown class and percent defect. The variables are not available in the growth prognosis model (Stage 1973) in which these models are to be used. Further, percent defect frequently is not measured in forest surveys. Thus, the alternative models in table 4 were developed using more available independent variables.

Table 2.--*Mortality models for north Idaho species*

Species:	*Pinus monticola* (western white pine)	
Prediction equation:	$1/\{1+\exp[3.25309-0.00072647(BA)+0.0166089(DBH)]\}$	
No. of observations:	1,363	
Variable	*Mean*	*Standard deviation*
BA - basal area/acre (ft^2/acre)	235.0	100.0
DBH - diameter at breast height (inches)	23.1	10.4
Species:	*Larix occidentalis* (western larch)	
Prediction equation:	$1/\{1+\exp[3.8774+0.2177(DBH)-0.0002209(HT)-0.02409(AGE)]\}$	
No. of observations:	784	
Variable	*Mean*	*Standard deviation*
HT - height (feet)	122.1	33.1
AGE - age (total years)	129.1	41.8
DBH - diameter at breast height (inches)	19.5	8.5
Species:	*Pseudotsuga menziesii* (Douglas-fir)	
Prediction equation:	$1/\{1+\exp[4.78313+0.21186(DBH)-0.039527(HT)]\}$	
No. of observations:	2,036	
Variable	*Mean*	*Standard deviation*
DBH - diameter at breast height (inches)	16.3	8.6
HT - height (feet)	88.8	34.8
Species:	*Abies grandis* (grand fir)	
Prediction equation:	$1/\{1+\exp[4.89819-0.0047554(\%DEF)-0.222746(CC)]\}$	
No. of observations:	3,864	
Variable	*Mean*	*Standard deviation*
%DEF - percent defect (appendix)	26.2	35.5
CC - crown class (1,2,3,4)	1.6	1.3
Diameter at breast height (inches)	18.0	10.59
Species:	*Thuja plicata* (western redcedar)	
Prediction equation:	$1/\{1+\exp[5.99811-0.01037(\%DEF)-0.26124(CC)]\}$	
No. of observations:	3,282	
Variable	*Mean*	*Standard deviation*
CC - crown class (1,2,3,4)	1.7	1.4
%DEF - percent defect (appendix)	40.9	39.4
Diameter at breast height (inches)	24.7	16.1

Table 3.--*Mortality rates for north Idaho species (no significant independent variables)*

Species:	*Tsuga heterophylla* (western hemlock)		
Mortality rate:	0.01355/yr		
No. of observations:	255		
Variable		*Mean*	*Standard deviation*
Diameter at breast height (inches)		16.9	11.9
Species:	*Pinus contorta* (lodgepole pine)		
Mortality rate:	0.00631/yr		
No. of observations:	178		
Variable		*Mean*	*Standard deviation*
Diameter at breast height (inches)		9.9	4.3
Species:	*Picea engelmannii* (Engelmann spruce)		
Mortality rate:	0.01987/yr		
No. of observations:	325		
Variable		*Mean*	*Standard deviation*
Diameter at breast height (inches)		17.2	8.7
Species:	*Abies lasiocarpa* (subalpine fir)		
Mortality rate:	0.02571/yr		
No. of observations:	145		
Variable		*Mean*	*Standard deviation*
Diameter at breast height (inches)		13.9	6.2
Species:	*Pinus ponderosa* (ponderosa pine)		
Mortality rate:	0.00949/yr		
No. of observations:	254		
Variable		*Mean*	*Standard deviation*
Diameter at breast height (inches)		18.4	9.3

Table 4.--*Alternative mortality models for grand fir and western redcedar*

Species:	*Abies grandis* (grand fir)
Prediction equation:	$1/\{1+\exp[4.8690+0.009915(HT)-0.01417(BA)]\}$
Species:	*Thuja plicata* (western redcedar)
Prediction equation:	$1/\{1+\exp[3.3028+0.01899(HT)+0.01048(BA)]\}$

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APPENDIX

Instructions for Estimating Percent Defect
(reproduced from "Instructions for Forest Inventory of Potlatch Forests, Inc. Logging Units" as revised July 8, 1959)

INSTRUCTIONS FOR ESTIMATING DEFECT

Minimum Merchantable Cruising Standards

No green tree is to be considered to be a cull unless all logs in the tree, cruised separately on their own merits, are culls based on minimum Company scaling standards.

Minimum standards for logs of the mixed species is 1/2 of its gross volume must be merchantable; and for logs of the pine species, 1/3 of their gross volume must be merchantable for lumber. Individual logs of dead trees cruised for pulp content are considered merchantable if 50% of their gross volume is free of rot. Thus a tree, either green or dead, may be given a defect figure of 75% or even more if it has a log or two in it that barely meets minimum standards.

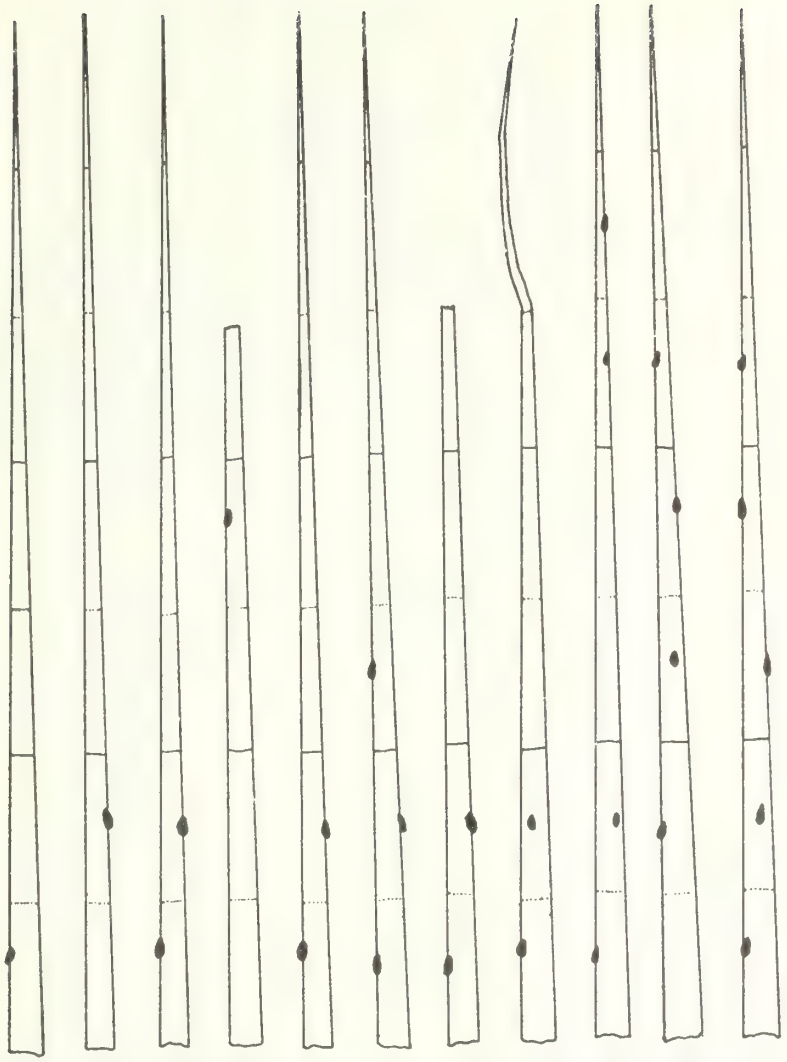
Dead Douglas-fir trees with few or no red needles, less than 22" DBH, will often be complete culls.

Sap-rotted trees - Reduce the diameter by 1/4 and the volume will be reduced by 1/2.

Minimum top diameters for white pine by DBH classes:

DBH	Top Dia.	DBH	Top Dia.	DBH	Top Dia.	DBH	Top Dia.
12	6	24	9	36	11	48	13
14	7	26	9	38	11	50	14
16	7	28	9	40	12	52	14
18	7	30	10	42	12	54	15
20	8	32	10	44	13		
22	8	34	11	46	13		

White Fir
A grandis



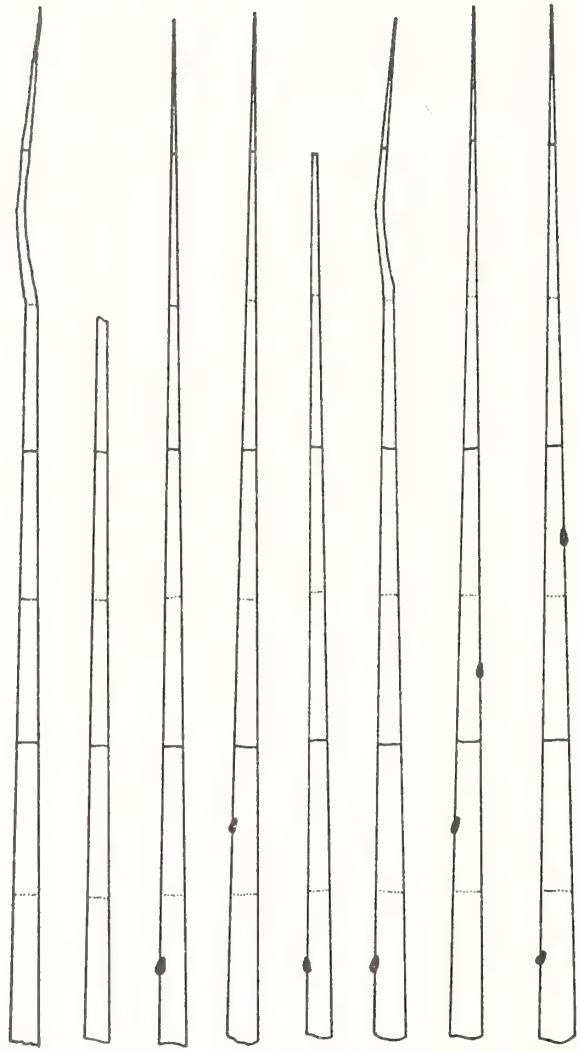
25% 25% 50% 50% 50% 75% 75% 75% 75% 75% 100% - % defect (lumber)

Average merchantable timber (6 logs). This roughly illustrates the % defect in 2nd growth white fir on average W.pine sites with regard to conk location. On white pine sites in mature timber, one conk (E. tinctorium) will cull one log in a white fir tree.

General notes on white fir:

1. 2nd and 3rd logs are most apt to be infected.
2. 50% of the volume is in the first long log (roughly).
3. Size of conk indicates to some extent the age of infection.
4. Broken tops, cat faces and frost cracks are also common indications of defect. The percent loss is indicated by the severity of the defect.
5. Appearance of bark sometimes gives indication of soundness of tree.

White fir A grandis



25% 25% 50% 75% 75% 75% 100% 100% - % defect (lumber)

This diagram shows the percent of lumber lost in white fir on all sites except white pine Sites I and II, and in over-mature timber on these good white pine sites, with regard to the fungus E. tinctorium.

1. If conk is on first log, cut 50% of tree volume.
2. If conk is on second or third log, cut 75% of tree volume.
3. If conk is on both second and third log, deduct 100%.
4. Rot extends 1 log below first visible conk and 1 log above last visible conk.

The above rules also apply to subalpine fir and western hemlock.

Western Red Cedar

Some average deductions for cedar:

Spike tops - 1-2 logs in old growth and 8' in 2nd growth.

Schoolmarms - 1-2 logs below fork in old growth. 8' in 2nd growth.

Knees - Indicate rot extends 1 log up and 1 log down from knee. (Generally joins other defect either above or below in tree.

Butt Rot - 1-2 logs in old growth. 8' in 2nd growth.

Defect in old-growth stand determined by:

A. Tree vigor as indicated by:
   1. Bark appearance
   2. Crown foliage (color & amount)
   3. Top (dead spike or alive)
   4. Limbs - cluster of dead ones in green crown.

B. Hollow Butts - These may be determined by sounding with ax, or seen through open cracks.

C. Schoolmarm tops & deformed trunks.

D. Cat faces (Fire Scars).

Defect in second-growth stand determined by:

A. Hollow Butts - Defect usually plays out in about 8'. Sometimes takes whole tree if tree vigor is unusually poor.

B. Schoolmarm tops, deformed trunks, spike tops. Deduct from 8' to 2 logs, rarely whole tree.

C. Cat faces, defect generally plays out within a few feet of exterior sign. If a cedar is vigorous, it will outgrow a cat face quicker and with less loss than our other species.

Notes on Cedar, T. plicata

Best old-growth cedar found on good, moist, well-drained sites. Rot is greatest on trees occupying low, flat, poorly-drained sites. The age of the trees is also an important factor regarding rot.

Old-growth climax stands are nearly always heavily infected with Poria weirii (yellow laminated rot). The fruiting body is located near root collar and is very hard to detect. Because conks are difficult to detect, rules for deductions on this basis cannot be made for cedar. This rot often causes the hollow butts of cedar, often runs into the second log and sometimes extends throughout the tree. So severe are the losses, caused largely by this fungus, that some climax stands (over mature) have been found to be about 65% defective on the stump.

Rot, in old-growth cedar that is forked within 30' of the butt, nearly always extends to the ground.

Defect will generally run 1-2 logs past exterior sign in old growth and 4-8' in second growth.

SIMPLIFIED RULES FOR DEDUCTIONS

Douglas Fir Western Larch Ponderosa Pine Lodgepole Pine White Pine (old growth) Grand Fir (2nd growth on W. Pine Site I & II) Spruce	Fungi - E. tinctorium - Fomes Pini - Deduct 1 log for 1 conk. (Cull each log that has 1 or more conks on it.) Figure rot extends 4' up and 6' down from conk, punk knot, or swollen knot.
Grand Fir (old growth & 2nd growth on all sites except W. Pine Site I & II) Alpine Fir Western Hemlock	Fungus - Echinodontium tinctorium Rot extends 1 log below first visible conk and 1 log above last visible conk.
Douglas Fir All Pines E. Spruce Larch	Fungus - Polyporuous Schweinitzil, velvet top fungus, causes butt rot. Deduct from 2'-8' (rarely more) depending on fungus development. 4' or 6% of tree volume will take care of most losses in 2nd growth, and 12% in old growth trees infected.
Western Larch	Defect - Massed pitch & shake. Mature and over-mature has this common defect and is evidenced by heavy butt swell and very thick ridges in bark of butt log. Defect generally sounds out where thick ridges in bark, and butt swell, stop.
White Pine (second growth)	Rot generally progresses from butt upward. Figure rot extends 2' up from highest conk and deduct portion of stem below this point. If only 1 conk is visible up on the stem, deduct 8' or 12% of tree's volume.

Log position in tree	Percentage distribution of gross merchantable volume (Scribner Decimal C) by logs, for trees* of indicated number of 16-foot logs per tree							
	2	3	4	5	6	7	8	9
	%	%	%	%	%	%	%	%
Butt	58	45	37	32	27	25	24	24
2	42	33	29	26	24	22	20	19
3		22	21	20	19	18	17	17
4			13	15	15	14	14	13
5				7	9	10	11	11
6					6	7	7	6
7						4	5	5
8							2	3
9								2
Tree total	100	100	100	100	100	100	100	100

* Includes following species: western white pine, ponderosa pine, white fir, Engelmann spruce, hemlock and larch.

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Hamilton, David A., Jr., and Bruce M. Edwards
1976. Modeling the probability of individual tree mortality. USDA For. Serv. Res. Pap. INT-185, 22 p. Intermountain Forest and Range Experiment Station, Ogden, Utah 84401.

This paper describes procedures for developing and testing models that predict the probability of individual tree mortality. The modeling procedures include data screening, parameter estimation, and model verification techniques that have been designed to deal with dichotomous dependent variables. To demonstrate the procedures, mortality models for 10 north Idaho species are developed and verified.

OXFORD: 562.22,--015.5
KEYWORDS: mortality, modeling, data screening, parameter estimation, model verification

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Headquarters for the Intermountain Forest and Range Experiment Station are in Ogden, Utah. Field programs and research work units are maintained in:

Billings, Montana
Boise, Idaho
Bozeman, Montana (in cooperation with Montana State University)
Logan, Utah (in cooperation with Utah State University)
Missoula, Montana (in cooperation with University of Montana)
Moscow, Idaho (in cooperation with the University of Idaho)
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AMERICAN REVOLUTION BICENTENNIAL
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GROWING
FROM
U.S. FORESTRY
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